Performance of an Analytical, Dual Infrared-Beam, Stored-Product Insect Monitoring System

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ABSTRACT A system is described for automated monitoring of pest insects in stored grain. It provides quantitative data indicative of the species of detected insects and is self-calibrating to maintain reliable operation over time across adverse environmental and biological conditions. The system uses electronic grain probes, each with a dual infrared-beam sensor head providing orthogonal views of falling insects. Sensor analog signals are analyzed by an embedded microprocessor, and extracted waveform parameters are transmitted back to a central computer. Filtering algorithms recognize and eliminate false detections due to extraneous (nonfalling) insect activities and provide an indication of species based on body size. Laboratory test data provide species identification templates and an analysis of Montana field test data acquired in aerated and nonaerated bins demonstrates the effectiveness of the filtering algorithms. The described system technology has been licensed by OPIsystems, Inc., Calgary, Alberta, Canada, and is commercially available as Insector.

KEY WORDS stored-product insects, automated monitoring, detection, grain probe trap, infrared sensors

Each year in the United States, losses due to damaged grain exceed $1 billion (Cuperus and Krischik 1995), and the worldwide annual cost of protecting bulk-stored agricultural commodities from infestations and direct losses caused by insects is far greater. Traditional practices for detecting and quantifying infestations involves visual inspection of grain samples and/or the contents of passive insect traps (Hagstrum et al. 1995). However, these practices are expensive, labor-intensive, and involve confined space entry safety issues. For these reasons, they are infrequently repeated, thus limiting the temporal availability of infestation data. As a result, insect control usually relies on scheduled prophylactic insecticide treatments. This strategy is becoming increasingly problematic because of new governmental restrictions and mandates (e.g., the Montreal Protocol; United Nations Environment Programme 2000) based on health and environmental concerns. In addition, the development of insect resistance is due to the overuse of insecticides and the lack of efficacy feedback to ensure adequate eradication.

In an integrated pest management (IPM) program, the underlying reason for monitoring insect populations is to make timely insect management decisions based on economic threshold analysis, i.e., projecting whether anticipated economic loss will be greater than the cost of enacting a control strategy (Hagstrum and Flinn 1995). Visual inspections of grain samples or traps' contents reveal numbers of insects and, to the trained eye, their species identity. When grain sampling is used, the insect numbers are directly translatable into population densities. Insect traps are far more sensitive to low population densities because they remain in the grain for extended periods, integrating insect captures over time. However, this complicates the interpretation of the insect trap captures, especially because they are affected by the disparate behaviors of the different species intermixed with varying environmental conditions (e.g., temperature and grain moisture content) that also affect behavior. In addition, knowledge of which species are present and their damage potential also may be important in performing economic threshold analyses. Internal feeders such as rice weevil, *Sitophilus oryzae* (L.), and lesser grain borer *Rhyzopertha dominica* (F.), are the primary cause of insect damaged kernels. External feeders such as red flour beetle, *Tribolium castaneum* (Herbst), sawtoothed grain beetle, *Oryzaephilus surinamensis* (L.), rusty grain beetle, *Cryptolestes ferrugineus* (Stephens), and flat grain beetle, *Cryptolestes pusillus* (Schöenherr), are considered secondary pests because they only feed on damaged kernels and other fine material.

To address the limitations of the traditional monitoring practices mentioned previously, several automated monitoring methods have been investigated

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(Shuman and Epsky 1999). In general, these incorporate some electronic sensing modality that responds to some aspect of the insects' presence or behavior to detect or preferably quantify infestations. Ideally, an array of sensor-triggered electronic eyes or cameras would be deployed throughout bins, sending back images for trained eyes or image analysis to decipher. However, this approach is currently not practical for economic and transmission bandwidth considerations. What has been attempted is the use of inexpensive acoustic (Hagstrum et al. 1996) and infrared-beam sensors (Shuman et al. 1996). Such sensors provide a squiggly line output signal that generally has been quantified by counting the number of spikes (i.e., waveform excursions beyond some threshold level). A major obstacle with this approach has been the confounding of the resulting output data due to the sensors' responses to other stimuli present or unpredictable insect behaviors.

One automated monitoring method was the electronic grain probe insect counter (EGPIC), a system that provided real-time monitoring with the use of infrared-beam sensor technology to detect and provide a time-stamped count for each insect entering any one of an array of modified grain probe traps distributed throughout bulk stored grain (Shuman et al. 1996, Litzkow et al. 1997). The EGPIC design has gone through several iterations (Shuman et al. 2001, Epsky and Shuman 2002) as the result of extensive testing (Brenner et al. 1998, Arbogast et al. 2000, Epsky and Shuman 2001, Toews et al. 2003, Epsky and Shuman 2004) that revealed quantitative performance errors under harsh field conditions (e.g., electric machinery noise, changing environmental conditions, and grain particles and dust).

Because all the versions of the EGPIC automated monitoring system described above generated one count (ideally) for each insect entering a probe, if the rates of insect counts were below an established threshold (e.g., based on factors such as economics or environmental parameters), no control action would be necessary. However, if the rate was above that threshold, the appropriate first response might have been to go into the commodity storage and identify the species at those probe sites that were getting the high insect counts. Then, with that species information, a decision could be made as to what control response was warranted. Thus, although the EGPIC system could eliminate the need to visually inspect the commodity on an ongoing scheduled basis, increasing insect counts may still have mandated visual sampling and interpretation before control decisions were made.

The EGPIC system used a sensitivity control so that it did not count objects (e.g., grain particles) smaller than the smallest stored-product insect of concern. Thus, smaller insects such as psocids (*Liposcelis* spp.) and mites [*Acarus siro* (L.)] would not be counted even though their presence may be of interest to the facility manager. This sensitivity control needed to be set conservatively (higher sensitivity) to ensure that each probe maintained a reasonable count accuracy with the smallest stored-product insect of concern (e.g., the flat grain beetle) because of the large electronic and mechanical component variability across probes. However, this occasionally led to false positives due to very small insects (e.g., psocids) and grain particles. Other potential sources of false positives were electrical impulse noise (e.g., generated by electric machinery) and a crawling or clinging insect managing to remain near the infrared beam, which can cause a multitude of false counts.

The above-mentioned shortcomings of the EGPIC system were addressed by the development of an analytical system incorporating sensor output analog processing (SOAP), an invention (Shuman and Crompton 2004) that used a microcontroller embedded in each probe to analyze the sensor's analog output signal and extract multiple waveform parameters for further processing back at a central computer. This methodology relied on the fact that there was more information in the sensor's squiggly line output signal than just the number of spikes. This additional information was exploited by computer intelligence programmed to recognize and filter out extraneous insect behaviors and other artifacts that had previously resulted in large numbers of false positives. The capabilities of this system, described by Shuman et al. (2004), also included probabilistic species identification of detected insects. The species identification system capability relied on a dynamic calibration methodology that insured all probes maintained matching effective response sensitivities in spite of large initial component tolerances and varying environmental conditions over long-term use.

The EGPIC system with SOAP species identification methodology relied upon the different sizes of the various stored-product insects. Insects crawling into the perforated probe body would then fall through a sensor head top funnel positioned just above a single horizontal infrared beam. Because these stored-product insects are all smaller than the ≈4.5-mm-diameter beam, a single insect would only block a fraction of the infrared light, resulting in a sensor output pulse with a peak amplitude (T_{PA}, target peak amplitude) directly related to the size of the insect and with a pulse duration (PD) equal to the time it took for the insect to fall through the beam. Although it was found that these T_{PA} values obtained with different species were significantly different from each other, the T_{PA} values acquired with any single species had a sizable variability that could be seen in an amplitude distribution histogram (see *Results*, Laboratory Tests). The overlap of amplitude distribution histograms plotted for different species represented an uncertainty in species identification. The broad width of the individual distributions was attributed to the random orientation of these nonspherical stored-product insects as they fell through the beam and to the insects' different paths through the nonuniform cross-sectional light intensity of the infrared beam.

This article describes the design, development, and field performance of a new patented invention (Shuman and Crompton 2005) that incorporates a dual

Fig. 1. Inside the probe sensor head (not shown), the orthogonal infrared-beam sources (clear LEDs) and receivers (dark phototransistors) are mounted on a ring connected to the microprocessor-based circuit board. A funnel is included for illustrative purposes to show how a falling insect (rice weevil) is directed (by a funnel shape in the sensor head) through the intersection of the beams.

infrared-beam sensor head to further enhance the performance of the EGPIC with SOAP system by improving its species identification accuracy and increasing the rejection of erroneous counts. The technology described in this article, incorporating EGPIC with SOAP and the dual beams, has been licensed from the USDA by OPIsystems, Inc., Calgary, Alberta, Canada, and is commercially available as Insector.

Materials and Methods

System Design. The major change introduced here is the redesign of the sensor head to incorporate a second horizontal infrared beam and the signal processing by using the resulting additional sensor data. This second beam intersects and is perpendicular to the first beam (Fig. 1) to provide an additional view of the falling insect from another orientation. Ideally, three orthogonal intersecting beams would provide the most information about the size of the falling insect. However, this was not implemented due to the practical consideration of not situating a beam transducer much below the upper funnel outlet hole where it would be prone to dust accumulation on its surface. In the current design, the four beam transducers (two light-emitting diode [LED] infrared sources and two phototransistor receivers) are recessed to the sides of the funnel outlet hole, away from the pathway of dust falling through the funnel. The funnel outlet hole needs to be smaller than the width of the infrared beam (4.5 mm) to ensure that any falling insect will pass through the beam. In the previous single beam sensor head design, the funnel outlet hole was elongated (3.2 by 6.4 mm) parallel to the length of the beam to help prevent clogging by larger objects while still ensuring insect detection. In the current dual-beam sensor head, the funnel outlet hole was reduced back to a circle (3.2 mm diameter) to ensure detection of falling insects by both beams. To help prevent clogging of this smaller funnel outlet hole, the insect entry holes in the probe body were reduced in size from 2.8-mm-diameter circles (Epsky and Shuman

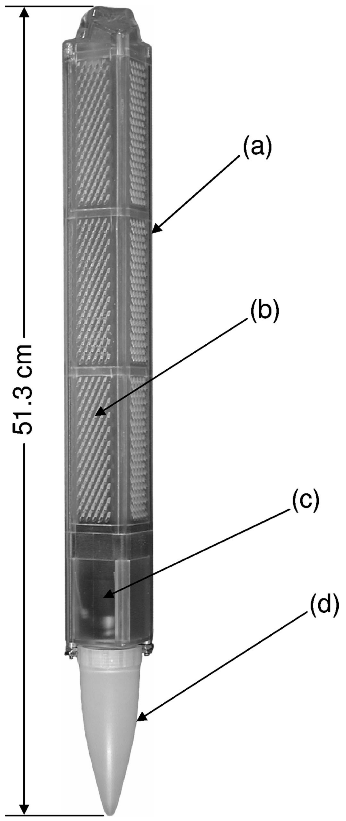

Fig. 2. Insector injection-molded electronic probe showing (a) probe body, (b) elliptical insect entry holes, (c) dual-beam sensor head with microprocessor-based circuit board, and (d) screw-on insect collection receptacle.

2002) to 1.6 by 2.8-mm ellipses, a shape made practical by injection-molded fabrication of the probe body (Fig. 2). This insect entry hole size was selected based on laboratory tests (unpublished data), indicating no reduction in insects' capabilities of crawling through these holes across the full range of stored-product insect sizes. As reported previously (Shuman et al. 2001), these insect entry holes are again slanted upward through the wall of the probe body so that gravity reduces the amount of debris migrating into the probe after its deployment in grain (an insertion tool with a sleeve covers the entry holes during probe insertion down into the grain). The 4.5-cm-square cross-sectioned body (for injection-molding considerations) has 1,080 insect entry holes over a 29-cm length resulting in a 51.3-cm-long fully assembled probe.

As was described in detail by Shuman et al. (2004) for the single infrared-beam system, a detection event occurred and a signal-present digital pulse (with a duration of PD) was generated whenever the sensor output signal exceeded a low-level detector threshold. The T_{PA} was measured during occurrence of the signal-present digital pulse. For each detection event, the four sensor waveform parameters measured by the microcontroller and transmitted back to the central computer were T_{PA}, PD, TL (the time elapsed since the end of the previous signal-present digital pulse), and an associated timestamp. For the dual-beam system, a detection event now occurs (Fig. 3) whenever the output signal from either or both beam sensors exceeds the low-level detector threshold. A composite signal-present digital pulse is generated with its leading edge corresponding to when the first sensor output signal exceeds the detector threshold and its trailing edge corresponding to when the last sensor output signal drops below the detector threshold. There is a target peak amplitude for each beam, T_{PA1} and T_{PA2}, measured during the occurrence of the composite signal-present digital pulse of duration PD. With TL and the event timestamp, there are now five parameters transmitted back to the central computer for each detection event.

The central computer completes the analysis of estimating the numbers and species of insects caught in each connected probe using these detection event parameters and that individual probe's calibration values. The same dynamic calibration methodology used to normalize the T_{PA} values across many probes' different response sensitivities and varying environmental conditions over longtime usage (as described in Shuman et al. 2004 for single beam sensor heads) is used for each of the two individual beams in the current sensor head, resulting in A_{PA1} and A_{PA2}, the adjusted target peak amplitudes for the two beams. Because the two views of the falling insect are orthogonal to each other, the composite adjusted target peak amplitude A_{PAC} can be calculated as the vector sum (Fig. 4) of the individual adjusted target peak amplitudes.

$$A_{PAC} = \sqrt{(A_{PA1})^2 + (A_{PA1})^2}$$

As a result of the dynamic calibration methodology, a 2.5-mm ball dropped through the center of the inter-

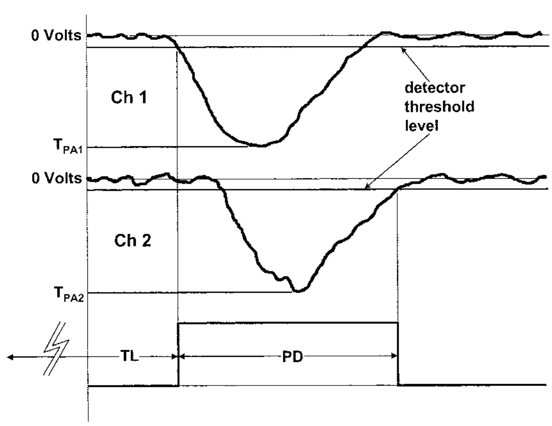

Fig. 3. Sensor waveforms from the two infrared-beam receivers generate the composite signal-present digital pulse when either or both exceed the detector threshold level. The four parameters extracted from the waveforms for each detection are the peak amplitudes T_{PA1} and T_{PA2}, the digital pulse duration PD, and the time since the previous digital pulse TL.

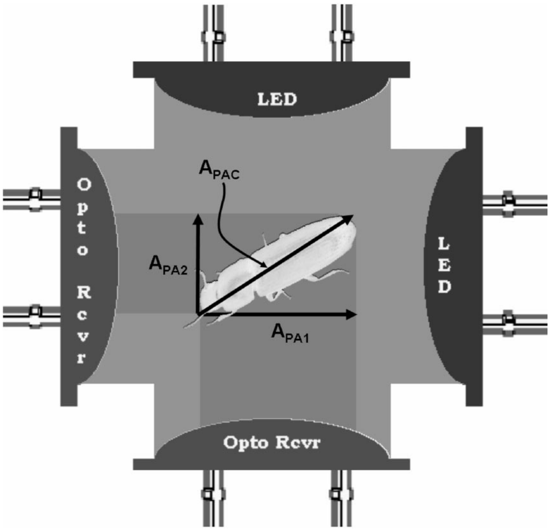

Fig. 4. Top-down view of an insect dropping through the orthogonal beams. The insect casts shadows on the two optical receivers (phototransistors), generating waveforms that result in the two adjusted target peak amplitudes (after calibration). The vector sum of these amplitudes yields the composite adjusted target peak amplitude proportional to the insect's body size.

section of the two beams of any probe will result in a A_{PAC} value of 100.

The rejection of potential false positives is still accomplished using the algorithms involving PD and TL described in Shuman et al. (2004), although PD is now for the composite signal-present digital pulse. Briefly, these algorithms reject pulses that have a PD that is outside the known range of time it takes for an object to fall through the infrared beams as well as rejecting pulse stream patterns indicative of insects loitering in beam pathways. In addition, with the dual-beam system, detections that occur on only one beam, indicative of an insect crawling on a beam transducer, are rejected.

Laboratory Tests. To quantify the dual-beam system's ability to discriminate among different stored product insect species, tests were conducted with 10 probes mounted in mini-silos filled with clean grain and then infested with a single species. Each test was conducted with 2–3 wk old laboratory reared adults of one of the following species: flat grain beetle, rusty grain beetle, sawtoothed grain beetle, lesser grain borer, red flour beetle, and rice weevil. In each test, count data (discussed above) were collected until >1,200 insect counts across probes were recorded. Histograms of adjusted peak amplitude distributions for each species were generated and then normalized for differences in numbers of counts across species to not bias the locations of distributions' crossings. To quantify the improvement in species discrimination with the dual-beam sensor head, amplitude histograms using data from only one of the two beams are compared with amplitude histograms by using the combined data from the two beams by calculating percentage of overlap of adjacent species' peak amplitude distributions.

Field Test. The field test was conducted at the Central Agricultural Research Center of Montana State University, located 3.3 km west of Moccasin, MT, during the 2003–2004 storage season. The concrete floor steel bins were built by Butler Manufacturing (Kansas City, MO) and were installed on-site in 1965. Two identical bins were used, and the bin dimensions were 3.9 m to the top of the sidewall with a 5.37-m diameter, giving a storage capacity of 68.4 metric tons. Overall height of the bins was 5.67 m, giving a bin volume of $\approx$106 m^3. One bin had been retrofitted for aeration using a portable four-branch cross-duct aeration system coupled to a 3-hp turbine fan (Keho Products Ltd., Barons and Nobleford, Alberta, Canada). The operation of the fan was controlled by software that automatically turned the fan on when the ambient air temperature was 2°C lower than the mean temperature in the center of the grain mass. The roof of each bin received three uniformly spaced, 30 by 30-cm, 70° angle airflow vents (CMC, West Fargo, ND). The bins each contained 65.3 metric tons of wheat, transferred to the bins in late August 2003. The wheat provided was U.S. No. 1, hard red winter wheat, harvested in late July 2003.

Each bin was equipped with five Insector probes embedded vertically so that the top of the probe was 30 cm below the surface of the grain. Probes were embedded using a custom designed insertion tool that covered the insect entry holes to keep grain out and that also has a bubble level to ensure probes were deployed vertically for proper operation. Four probes were located at the cardinal compass points, at 60 cm from the bin wall, and the fifth was in the bin center. The electronic captures were acquired on a remote computer. The probes were equipped with closed collection receptacles to be used in evaluating system performance. In commercial practice, a receptacle that allows insects to escape could be used to reduce bin entries for probe maintenance. A heavy cable with a terminal flag resting on the grain surface was used to locate and retrieve all traps. Insects captured in all traps were transferred to prelabeled scintillation vials containing 70% ethanol and taken to the laboratory for species determination. Captured insect counts were compared with electronic counts both before and after filtering algorithms were applied, using the regression analysis package TableCurve 2D (Systat Software, 2002).

Results

Laboratory Tests. The histograms of peak amplitude distributions for each species obtained with dual-beam sensor heads are shown in Fig. 5. Although the sample size for each species is different, the distributions are normalized so that the number of insects represented by each distribution (i.e., the sum of the data points or area under the distribution) is 1,000. The different species distributions are not uniformly spaced along the amplitude axis but rather seem to

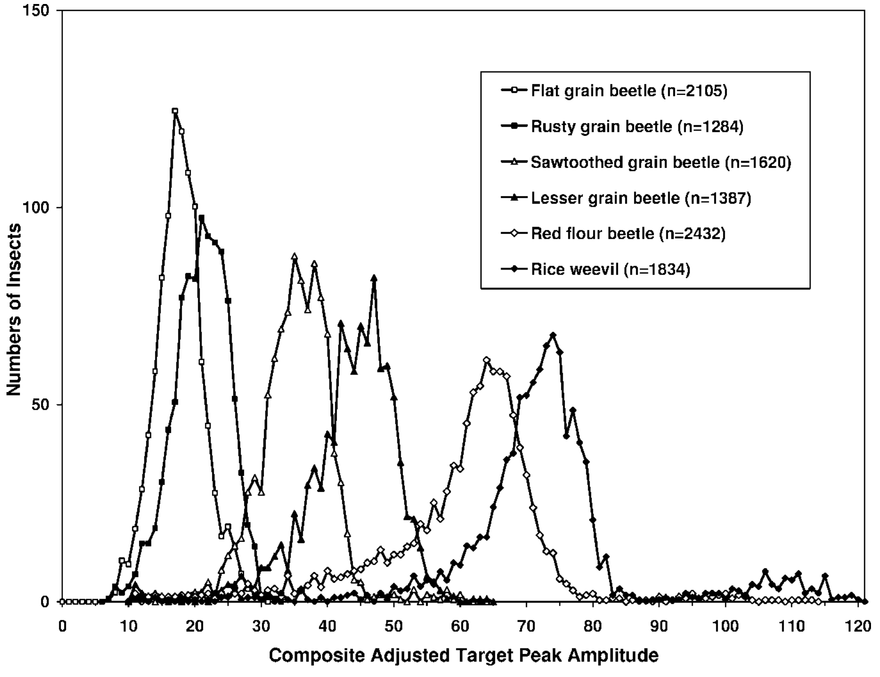

Fig. 5. Composite adjusted target peak amplitude distributions obtained for six different insect species by using probes with dual-beam sensor heads. The data were acquired from probes immersed in grain infested with one species at a time and then normalized to 1,000 insects per species.

separate into small, medium, and large groupings. The separations between these distributions are more clearly defined than those obtained with using the data from only one of the two beams (Fig. 6). The amount of distribution overlap represents the degree of uncertainty in identifying a detected insect's species.

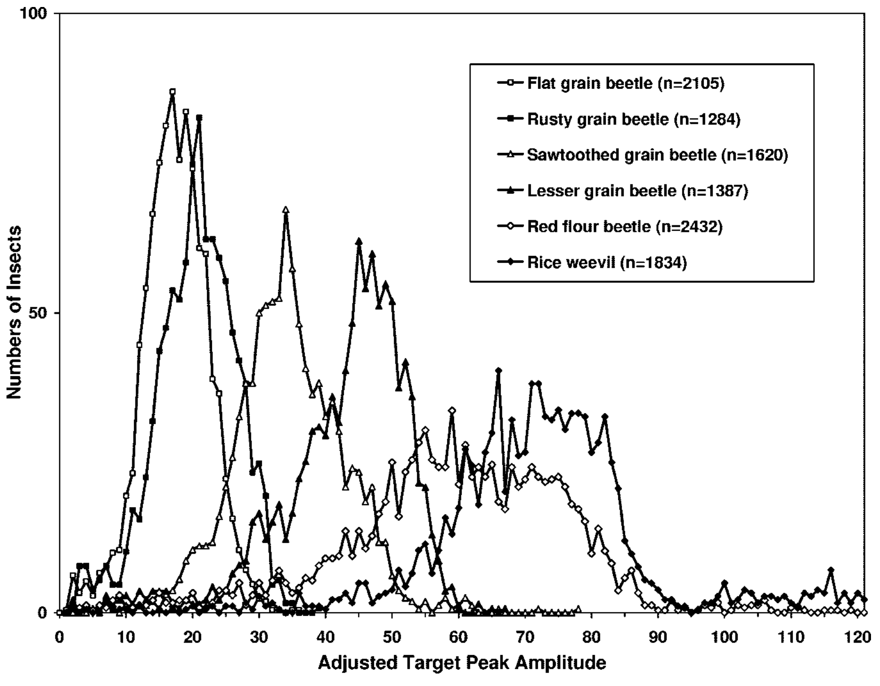

Fig. 6. Same as in Fig. 4 except now the adjusted target peak amplitude distributions are obtained with data from only a single infrared beam.

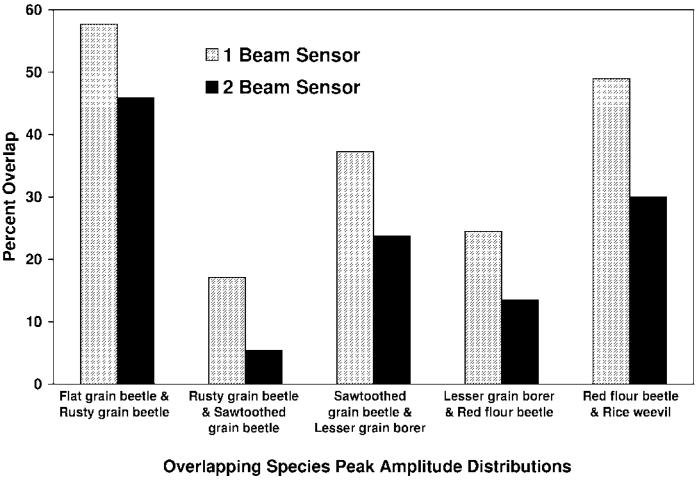

Fig. 7. Percentage of overlap (100 × intersection/union) of the adjacent peak amplitude distributions shown in Figs. 4 and 5.

This overlap is quantified by calculating the area ratio of the intersection to the union of each adjacent pair of amplitude distributions so that two identical distributions would result in a ratio of 1 or 100%. The relative overlap obtained with using data from both beams of the dual-beam sensor head compared with using single beam data are shown in Fig. 7. The largest overlap is between the flat grain beetle and rusty grain beetle distributions, not surprising because these species are similar in size and so closely related, making their discrimination less important from the viewpoint of the grain manager. The smallest overlap of adjacent distributions occurs between the rusty grain beetle and the sawtoothed grain beetle distributions. The mean difference provided by the dual-beam sensor head is a 36% decrease in overlap of adjacent distributions for the six species tested.

Field Test. Electronic counts were recorded from 29 August through 5 December 2003, except during some system problems and for a few hours each week when probes were removed from the grain mass for collection of insects from probes' receptacles. All totaled, there were 12 wk of electronic counts successfully acquired from the nonaerated bin and 11 wk from the aerated bin. One of the probes (east side) in the nonaerated bin was electronically noisy, and its data were eliminated from this analysis. The computer-controlled aeration fan was automatically activated during nine of the 11 wk electronic data were acquired. Subsequent examination of data acquired from the aerated bin revealed that operation of the fan produced excessive numbers of false counts. Thus, an initial analysis of system performance is based on 12 wk of data from the nonaerated bin and 2 wk of data from the aerated bin for total of 58 probe-weeks. For each probe-week, the number of raw (unfiltered) electronic counts are compared with the number of insects captured in that probe's receptacle and plotted as a data point in Fig. 8. As discussed previously, these raw electronic counts correspond to the number of spikes on the sensor's output signal. Linear regression analysis shows a poor consistency between electronic counts and captured insects ($r^2 = 0.46$) with an average number of counts per insect that is greater than five [$y = (5.18 \pm 0.75)\ x + (72.58 \pm 10.59)$; $F = 48.2$; df = 1, 56; $P = < 0.0001$]. These results are reminiscent of performances encountered under field conditions (unpublished data) since the inception of electronic probe field tests over a decade ago.

The electronic data were next analyzed using the filtering algorithms discussed previously. Because all of the insects captured were rusty grain beetles, which is typical for this geographic location, the filtering algorithm was set to only consider electronic counts with A_{PAC} values within a range of 8–34 (Fig. 5). The upper end of this range would be set slightly lower (e.g., 28) if it was known that sawtoothed grain beetles were present. The results after filtering also are plotted in Fig. 8 by using a secondary vertical axis. Now the linear regression shows an excellent consistency between electronic counts and captured insects ($r^2 = 0.99$) with almost a one-to-one correspondence [$y = (1.01 \pm 0.01)\ x + (0.42 \pm 0.20)$; $F = 5320$; df = 1, 56; $P = < 0.0001$]. It is noted that one of the data points, corresponding to 1 wk for the probe in the middle of the nonaerated bin, had 88 insects and 88 filtered electronic counts. Because 30 was the next highest number of insects captured during a 1-wk interval, there may be concern that this could be driving the regression line. To address this, additional regression analyses are performed for the raw and filtered data without including this point of greater capture magnitude. Although the effect of removing this data point was noticeable with the raw electronic counts [$y = (7.68 \pm 1.30)\ x + (64.36 \pm 10.82)$, $r^2 = 0.39$; $F = 34.8$; df = 1, 55; $P = < 0.0001$], the very slight decrease in overall performance results with the filtered electronic counts [$y = (1.06 \pm 0.02)\ x + (0.27 \pm 0.20)$, $r^2 = 0.97$; $F = 1920$; df = 1, 55; $P = < 0.0001$] indicates that the system operated at a high level of accuracy

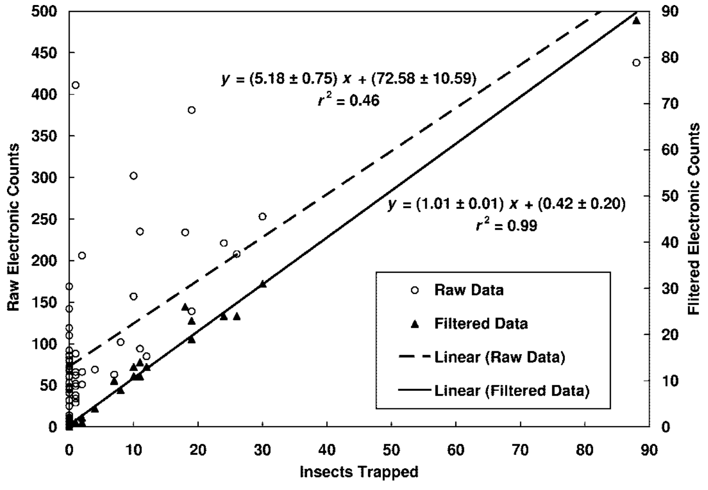

Fig. 8. Montana field test data (58 probe-weeks) were collected from probes not exposed to aeration. Each data point corresponds to the cumulative counts over a 1-wk period for one probe. Both raw and filtered electronic counts are compared with actual numbers of insects trapped.

when insects were scarce as well as when they were more abundant.

In an effort to use electronic count data from the aerated bin, these data were analyzed as a function of the turn-on and turn-off times of the fan. Fortunately, those fan times were electronically recorded by the same computer clock used to time stamp the probes' electronic counts. This permits time-synchronized summation across probes and numbers of times the fan turned on during the week since the last insertion of probes. Using 1-min time interval resolution, the cumulative count data for 45 probe-insertions are plotted in Fig. 9. Also plotted is the number of counts recorded during the interval from 1 min before until 1 min after the turn-off time of the fan. The bar graph shows the largest number of false counts occurs after the first onset of the fan after probe insertion and diminishes with each subsequent onset if the probe is not moved. It is recognized that these counts are primarily due to grain debris being blown into the probe. Because the

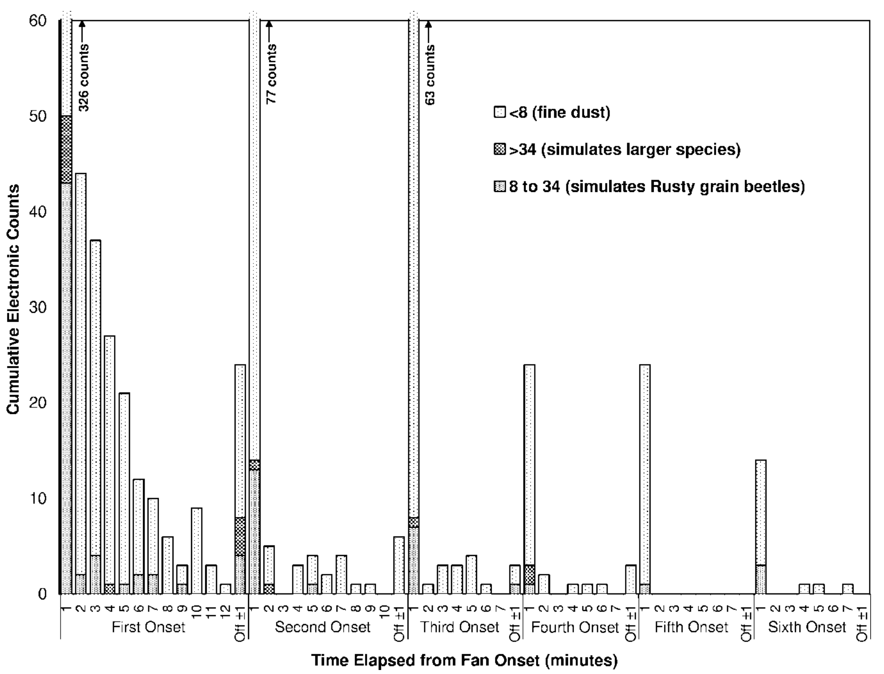

Fig. 9. Cumulative counts over 45 probe-weeks (45 probe insertions) due to aeration fan operation. Although most detected objects are too small to be insects, substantial numbers are large enough to be identified as (simulate) insects.

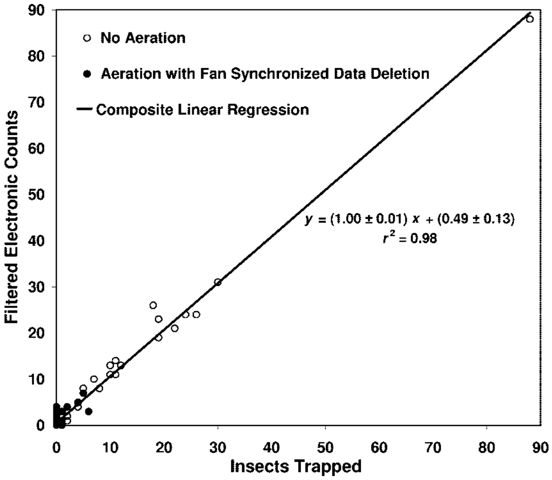

Fig. 10. Overall (103 probe-weeks) field test performance using combined data from probes exposed (data removal synchronized to fan operation is used) and not exposed to aeration.

fan is blowing air upwards through the bin, the probes are especially vulnerable to debris counts because the entry holes slope upward into probes. Although most of the debris is composed of dust particles too small to be insects ($A_{PAC} < 8$), there are substantial numbers of particles large enough to simulate rusty grain beetles and even larger insects. Although deleting all electronic counts while the fan is running would eliminate these false counts, valid insect counts also might be missed during long fan runs. The data in Fig. 9 show a rapid decay in numbers of counts shortly after the fan turns on. Based on this, electronic counts during the first 15 min after fan turn-on and from 1 min before until 1 min after fan turn-off were deleted. Using this method, the remaining data from the aerated bin were filtered and combined with the previously filtered data shown in Fig. 8 to calculate the composite linear regression line in Fig. 10 encompassing 103 probe-weeks of acquired data. The addition of data from the aerated bin yielded similar regression analyses results [$y = (1.00 \pm 0.01)\ x + (0.49 \pm 0.13)$, $r^2 = 0.98$; $F = 6910$; df = 1, 56; $P = < 0.0001$]. Once again, the point of greater capture magnitude was removed and the regression analysis repeated to observe that point's limited influence. As before, this resulted in a very slight decrease in overall performance [$y = (1.04 \pm 0.02)\ x + (0.43 \pm 0.13)$, $r^2 = 0.96$; $F = 2590$; df = 1, 55; $P = < 0.0001$].

Discussion

The new Insector System incorporating probes with dual infrared-beam sensor heads and SOAP has advanced the reliability and performance of automated insect monitoring for stored products. The peak amplitude distributions obtained in the laboratory can be used as templates to indicate the species of detected insects. Although this species identification may still not be performed with absolute certainty, the use of two orthogonal beams reduces the overlap of the peak amplitude distributions, substantially improving the confidence of its estimate. This confidence can be further increased at commercial sites based on the knowledge of which species are commonly found in those geographic locations. When used with closed insect capture receptacles, substantial electronic insect counts can be followed by bin entries to validate or adjust use of electronic data in species identification. As experience is gained with patterns of insect behavior, such as aggregation and species interactions, groupings of peak amplitude data points may begin to resemble template distributions, giving further confidence in identifying species. It may even be appropriate to generate custom template distributions by dropping site insects through probes to take into account the different size ranges of native populations that result from local environmental conditions.

Performance under harsh field conditions has always been problematic with the various versions of the EGPIC systems (Arbogast et al. 2000, Toews et al. 2003). The Insector system test in Montana produced insect counting performance never before achieved in the field. The most significant feature of the new system is its ability to discriminate between falling insects and other insect activities. This is based on algorithms developed in the laboratory to recognize sensor output signal patterns corresponding to these other activities. These algorithms are programmed into the computer by using adjustable parameters that can be empirically tuned over time to become more effective in filtering out false positives. One of the most effective parts of this filtering, only possible with this new dual-beam system, is the rejection of detections that only occur on a single beam. This virtually eliminates false counts due to an insect crawling around inside the sensor head, something that has previously been virtually impossible to prevent under field conditions.

In the Montana field test data set, the clustering of aeration data points near the origin compared with the nonaeration data points (Fig. 10) indicates that aeration is a viable insect control method in that climate. As would be expected, the largest insect counts (e.g., the outlying data point) occurred in the middle of the nonaerated bin, where it is warmest. Although the peak amplitude data were used in filtering out false counts, this field test did not demonstrate the system's ability to discriminate among species because only one species was present. Clearly, extensive field testing in different geographic locations is needed. One of the things uncovered in this field test was the effect of grain disturbance on system performance. Workers walking in the bins generated many false counts, but these only occurred at the beginning and end of the week-long testing periods and were readily deleted out of the raw data file. Aeration also disturbed the grain, but fortunately during this field test the fan activity was logged with time stamps, allowing for synchronized partial deletion of counts. In Montana, like for most northern grain-producing areas, there is a trend toward using larger fan capacities to dry grain that is harvested late. Therefore, the air velocity used is greater than what is typically encountered in more southerly climates where further system field testing may warrant the reduction of the fan operation data deletion time, thereby reducing loss of valid insect counts. Automated deletion of counts acquired during grain disturbances also may be achieved by deploying vibration sensors in the grain. These could be calibrated to remove probe count data whenever grain vibration exceeds an amount experimentally determined to introduce grain debris into probes.

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References Cited

Arbogast, R. T., P. E. Kendra, D. K. Weaver, and D. Shuman. 2000. Insect infestation of stored oats in Florida and field evaluation of a device for counting insects electronically. J. Econ. Entomol. 93: 1035–1044.

Brenner, R. J., D. A. Focks, R. T. Arbogast, D. K. Weaver, and D. Shuman. 1998. Practical use of spatial analysis in precision targeting for integrated pest management. Am. Entomol. 44: 79–101.

Cuperus, G. W., and V. A. Krischik. 1995. Why stored product integrated pest management is needed, pp. 199–200. *In* Stored Product Management, E-912. Oklahoma State University, Cooperative Extension Service, Stillwater, OK.

Epsky, N. D., and D. Shuman. 2001. Laboratory evaluation of an improved electronic grain probe insect counter. J. Stored Prod Res. 37: 187–197.

Epsky, N. D., and D. Shuman. 2002. Hole density and capture of stored-product insects pests in grain probe traps. J. Econ. Entomol. 95: 1326–1332.

Epsky, N. D., and D. Shuman. 2004. Arena size, hole density, and capture of *Oryzaephilus surinamensis* (Coleoptera: Silvanidae) in grain probe traps. J. Econ. Entomol. 97: 150–154.

Hagstrum, D. W., and P. W. Flinn. 1995. IPM in grain storage and bulk commodities, pp. 201–206. *In* Stored Product Management, E-912. Oklahoma State University, Cooperative Extension Service, Stillwater, OK.

Hagstrum, D. W., P. W. Flinn, and W. S. Fargo. 1995. How to sample grain for insects, pp. 65–70. *In* Stored Product Management, E-912. Oklahoma State University, Cooperative Extension Service, Stillwater, OK.

Hagstrum, D. W., P. W. Flinn, and D. Shuman. 1996. Automated monitoring using acoustical sensors for insects in farm-stored wheat. J. Econ. Entomol. 89: 211–217.

Litzkow, C. A., D. Shuman, S. Kruss, and J. A. Coffelt. 1997. Electronic grain probe insect counter (EGPIC). U.S. Patent No. 5, 646: 404.

Shuman, D., and R. D. Crompton. 2004. Sensor output analog processing: a microcontroller-based insect monitoring system. U.S. Patent No. 6,707,384 B1.

Shuman, D., and R. D. Crompton. 2005. Sensor output analog processing: a microcontroller-based insect monitoring system. U.S. Patent No. 6,882,279 B2.

Shuman, D., and N. D. Epsky. 1999. Computerized monitoring of stored-product insect populations, pp. 1429–1436. *In* J. Zuxun, L. Quan, L. Yongsheng, T. Xianchang, and G. Lianghua [eds.], Proceedings of the 7th International Working Conference on Stored-Product Protection. Sichuan Publishing House of Science and Technology, Chengdu, China.

Shuman, D., J. A. Coffelt, and D. K. Weaver. 1996. A computer-based electronic fall-through probe insect counter for monitoring infestation in stored products. Trans. ASAE 39: 1773–1780.

Shuman, D., D. K. Weaver, and R. T. Arbogast. 2001. A computer-based insect monitoring system for stored-grain using infrared sensors. Acta Hortic. 562: 243–255.

Shuman, D., R. G. Larson, and N. D. Epsky. 2004. A quantitative store-product insect monitoring system using sensor output analog processing (SOAP). Trans. ASAE 347: 1857–1864.

SYSTAT Software. 2002. TableCurve 2D, version 5.01, SYSTAT Software, Inc., Richmond, CA.

Toews, M. D., T. W. Phillips, and D. Shuman. 2003. Electronic and manual monitoring of *Cryptolestes ferrugineus* (Coleoptera: Laemophloeidae) in stored wheat. J. Stored Prod. Res. 39: 541–554.

United Nations Environment Programme. 2000. The Montreal protocol on substances that deplete the ozone layer. Ozone Secretariat, United Nations Environment Programme, Nairobi, Kenya.

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